

# Quality Indicators for Learning Analytics

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## Quality Indicators for Learning Analytics

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### ABSTRACT

This article proposes a framework of quality indicators for learning analytics that aims to standardise the evaluation of learning analytics tools and to provide a mean to capture evidence for the impact of learning analytics on educational practices in a standardised manner. The criteria of the framework and its quality indicators are based on the results of a Group Concept Mapping study conducted with experts from the field of learning analytics. The outcomes of this study are further extended with findings from a focused literature review.

### Keywords

Learning analytics, Quality indicators, Group concept mapping, Framework

### Introduction

In the last few years, the research field of learning analytics (LA) has been growing steadily. According to Siemens (2011) LA is “the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimising learning and the environments in which it occurs”. Building on ideas from process mining, data processing, information retrieval, technology-enhanced learning, educational data mining, and visualisation LA is a multi-disciplinary research field that now forms its own domain. Several resources and organisations are already dealing with the topic in special journal issues, conferences, workshops as well as courses, summer institutes, and societies (SoLAR, n.d.) specifically dedicated to LA. There, the research community has worked on the state of the art in learning analytics, its processes, frameworks, definitions, and challenges (see Clow, 2012; Drachsler & Greller, 2012; Duval, 2011; Elias, 2011; Ferguson, 2012a; Ferguson, 2012b; Greller & Drachsler, 2012; Siemens & Baker, 2012).

Making use of learning analytics can give added value to learners as well as educators. Many university courses today consist of a blended approach between classroom lectures and self-regulated learning activities. LA can help learners to better plan and reflect these activities by becoming aware of their actions and learning processes. According to Endsley (1995, 2000) being aware of one’s own situation is a three level process and a prerequisite for making decisions and effectively performing tasks: the perception of elements in the current situation is followed by the comprehension of the current situation which then leads to the projection of a future status. Once a learner is aware of his situation, he “reflects on the phenomenon before him, and on the prior understandings which have been implicit in his behaviour” (Schön, 1983) to then engage in a process of continuous learning. Reflection can promote insight about something that previously went unnoticed (Bolton, 2010) and lead to a change in learning behaviour. Thus, results of LA can be used to foster awareness and thus reflection (Verpoorten, Westera, & Specht, 2011; Verpoorten, 2012; Govaerts, Verbert, Duval, & Pardo, 2012) or to give recommendations for further steps in a current learning scenario (Greller & Drachsler, 2012). As Ferguson (2014) explains, LA offers “ways for learners to improve and develop while a course is in progress. These analytics do not focus on things that are easy to measure. Instead, they support the development of crucial skills: reflection, collaboration, linking ideas and writing clearly”. Awareness and reflection support for students are consequently highly important aims of learning analytics. The existence and impact of these aims, however, are hard to measure due to the lack of standards that the student support of LA tools can be measured against.

The same applies to educators. In order to support students within a course, teachers should be aware of what the students are doing, how they are interacting with the course material, where comprehension problems arise (cf. Scheffel et al., 2011; Scheffel et al., 2012). Especially if the number of students in a course is high and the tasks the students are engaged in are not trivial, teachers need assistance for keeping track of the students’ activities, e.g., with the help of activity-based learner-models (Florian, Glahn, Drachsler, Specht, & Fabregat, 2011). Zinn & Scheuer (2006) conducted a survey among teachers trying to identify requirements for student tracking tools. Among the information deemed mostly important were the students’ overall success rate, the mastery level of concepts, skills,

methods and competencies as well as the most frequently diagnosed mistakes. Such information is also needed for the evaluation of a course, i.e., didactic concept, materials, contents, tools, and tests. Awareness and reflection support for educators are thus also highly important aims of LA. But as with the learner support, standards that define quality indicators for learning analytics tools are missing.

While the added value of LA for learners and educators is clearly recognised (Long & Siemens, 2011), little research has been done so far to compare the findings of empirical LA studies and their tools as having a desirable effect on learning. This article therefore proposes to work toward quality indicators for learning analytics that will help standardise the evaluation of LA tools. It provides a first version of a framework of quality indicators to measure and compare the impact of LA on educational practices.

The quality indicator framework has been developed with experts from the LA domain by using a Group Concept Mapping (GCM) approach. The remaining parts of the article are organised in the following way: First, we will present the GCM methodology and provide some demographic description of the participants. Second, we will present and discuss the empirical findings of the study that reflect the LA community's view on such quality indicators. Third, we will propose a first version of a framework of quality indicators for learning analytics. Fourth, we will further extend the findings of the GCM study with a focused literature study of related articles. Finally, we will conclude our results and provide some limitations and potential future research directions toward the application of the quality indicators in learning analytics.

## Group Concept Mapping

### Method

One methodology to identify a group's common understanding of a given issue is Group Concept Mapping. It is a very structured approach that applies quantitative as well as qualitative measures that create a stakeholder-authored visual geography of ideas from a target group, combined with specific analysis and data interpretation methods, to produce maps to guide planning and evaluation efforts on the issues of the group (Kane & Trochim, 2007). Our study makes use of a GCM online tool (Concept Systems Global, n.d.) and consists of three steps for the participants: (1) generation of ideas, i.e., quality indicators of learning analytics, (2) sorting of the collected ideas into clusters, and (3) rating of the ideas according to several values, e.g., importance and feasibility. The individual input of the participants is aggregated to reveal shared patterns in the collected data by applying statistical techniques of multidimensional scaling and hierarchical clustering. Visualisations then help to grasp the emerging data structures and to interpret the data. One important aspect of GCM is its bottom-up approach. Instead of presenting a given set of criteria to sort and rate, the community itself generates the ideas that are to be clustered and rated by a group of experts.

### Participants

The involvement of participants in our GCM study was twofold (see Table 1). The first phase was conducted during the days of the Learning Analytics and Knowledge Conference 2014. Calls for participation were circulated via several channels, e.g., Twitter, project websites, personal contact, email etc., asking people involved and interested in LA to contribute their quality indicators for learning analytics to the brainstorming phase. Participation was accessible via a link and open, i.e., people did not have to register with the GCM tool. In total, 74 people participated in the brainstorming phase.

**Table 1: Overview of participants of the GCM study**

	Started	Finished
Brainstorming	74	74
Demographic questions	33	24
Sorting	33	23
Rating importance	24	21
Rating feasibility	22	20

For the second phase, i.e., sorting and rating of the collected quality indicators, we selected 55 experts from the domain of LA (i.e., they had been involved in the domain for several years, had published about learning analytics-related topics, were from the higher education sector and preferably had a PhD degree) and contacted them personally. Table 2 shows a summary of the demographics, the average expert of the study is a researcher at a university with an advanced expertise in LA and has more than six or ten years of work experience.

**Table 2: Answers to demographic questions by participants of phase two**

Participant Question	Option	Frequency	%
Expertise	Novice	0	0.00
	Intermediate	6	25.00
	Advanced	11	45.83
	Expert	7	29.17
		24	100.00
Experience	Less than 5 years	8	33.33
	6-10 years	5	20.83
	More than 10 years	11	45.83
		24	100.00
Involvement	More in research	16	66.67
	More in teaching	1	4.17
	Equal in research and teaching	4	16.67
	Other	3	12.50
		24	100.00

## Procedure

All participants of all three activities were informed about the purpose, the procedure, and the time needed to complete the activities. Participants of the first phase were given a link to access the brainstorming section of the GCM tool and asked to generate ideas by completing the following statement: *"One specific quality indicator to evaluate the effects of learning analytics is ..."*. Participants had ten days to contribute to the brainstorming. During this first phase the 74 participants generated a total of 92 original ideas. Before releasing the list of statements into the second phase, identical statements were unified and too vague ideas, e.g., „Range of flexibility in moving from one point to another in a theoretical discussion“, were taken out by us. Also, those statements that contained more than one idea were split, e.g., “students and teachers change their behaviour in some aspects” was split into one statement for teachers and one for students. After the cleaning process, the now 103 statements (the full list is available at <http://bit.ly/103QILA>) were randomised and pushed into the sorting and rating phase. Participants first sorted the statements according to their view of the statements’ similarity in meaning or theme and to also name the clusters. Dissimilar statements were not to be put into a “miscellaneous” cluster but rather into their own one-statement-cluster in order to ensure statement similarity within the clusters. Then, participants rated all quality indicators on a scale of 1 to 7 according to their *importance* and *feasibility*, with 1 being of lowest and 7 being of highest importance/feasibility. Participants had two weeks to complete the sorting and rating activities.

## Results

### Point Map

The GCM tool offers a number of automated analyses of the collected data: multidimensional scaling and hierarchical clustering for the sorting data and mean, standard deviation and correlation for the rating data. Figure 1 shows a point map of the 103 quality indicators, i.e., the outcome of the multidimensional scaling analysis. The multidimensional scaling analysis assigns a so-called bridging value between 0 and 1 to each statement. Statements with low bridging values have been grouped very close together with other statements around it, e.g., statements 98, 52, 75, 99 on the lower right side of Figure 1 all deal with some form of student motivation and can be considered quite coherent. Statements with higher bridging values can also be grouped together but the surrounding statements are then further apart, e.g., statements 95, 23, 50, 61 about teacher motivation, engagement and feedback. Thus, statements that are close to one another in the map are also close to one another in meaning and have thus been clustered together by the experts.

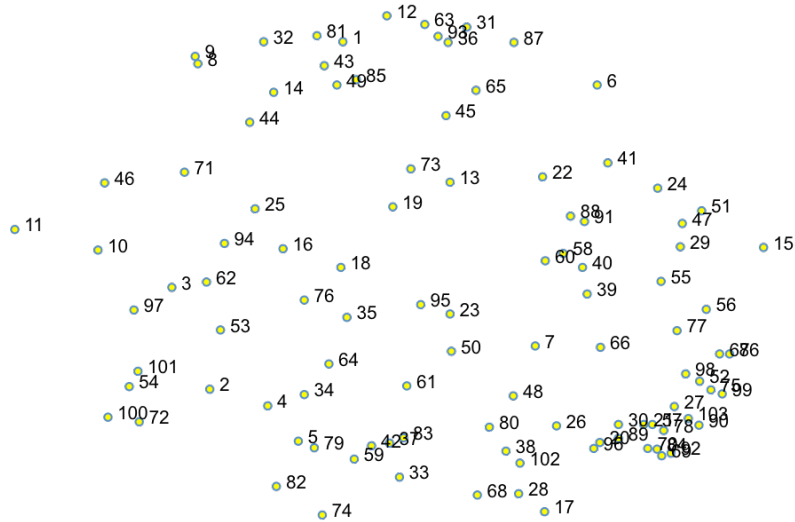


Figure 1: Point map of the 103 quality indicators

### From Point Map to Cluster Map

In some areas of the map it is quite easy to detect groups by simply looking at the point map. In other areas, however, it is more difficult to decide where group boundaries could be. The hierarchical clustering analysis of the GCM tool offers several solutions to a given point map. We used a cluster replay map, starting at 15 clusters and working down to two (see Figure 2). For each cluster-merging step we carefully looked at the statements of the clusters that were to be combined to check whether a merging made sense. The solution that seemed best to be representing the collected data and the purpose of the study was the one with eight clusters.

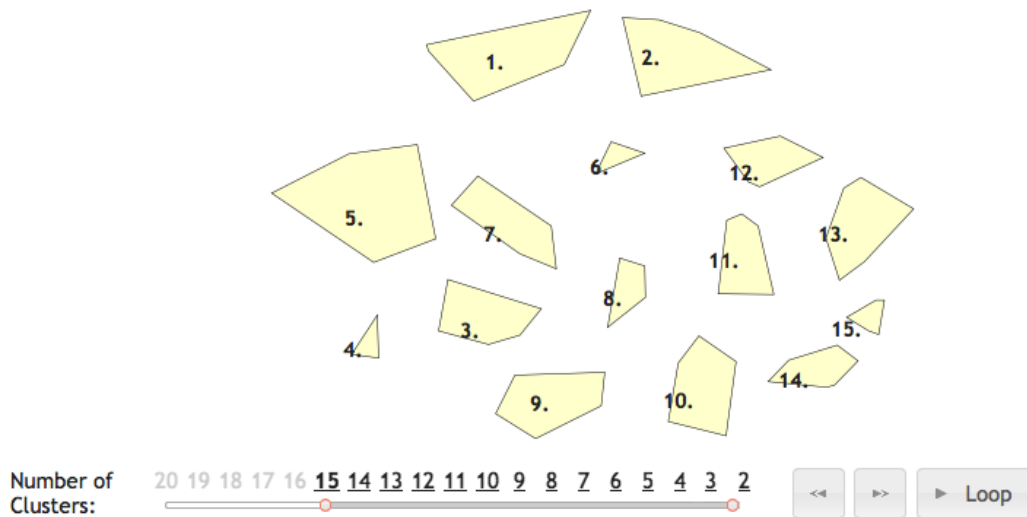


Figure 2: Replay map showing 15 clusters

After deciding on the number of clusters to work with, meaningful labels needed to be constructed for the clusters. The system automatically suggests a list of labels per cluster. Another way of finding appropriate labels is to look at the bridging values of the statements within a cluster. The lower the bridging values are, the better do those statements define the cluster. A third way to find meaningful cluster labels is to find the overarching theme of a cluster by looking at all statements of a cluster. We combined all three methods to define the labels of the 8-cluster solution (see Figure 3): 1. *Data: open access*, 2. *Data: privacy*, 3. *Acceptance & uptake*, 4. *Learning outcome*, 5. *Teacher awareness*, 6. *Learning performance*, 7. *Learning support*, and 8. *Student awareness*.

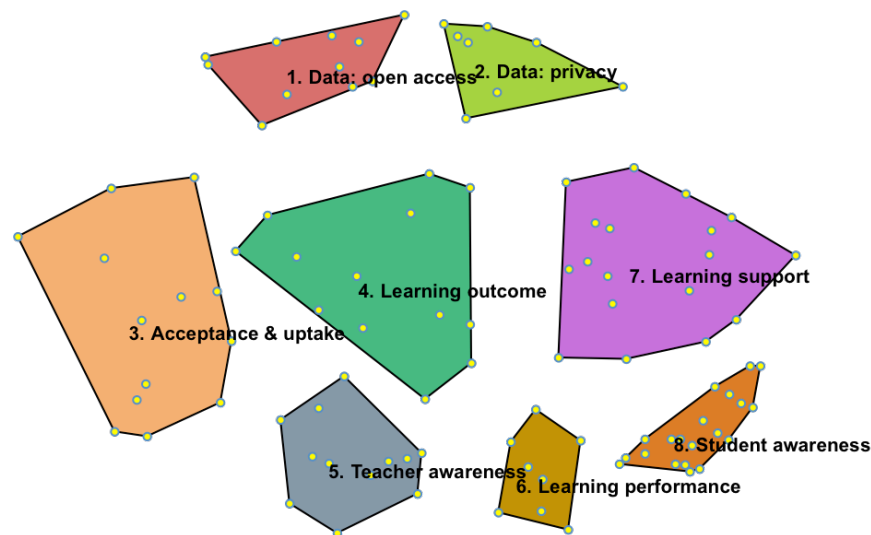


Figure 3: Cluster map with labels

The GCM tool assigns each cluster with a bridging value. The more coherent a cluster is, the lower is its bridging value which can be attributed to a high agreement rate from the experts about statements within a cluster. The four most coherent clusters are *Student awareness* (0.11), *Data: open access* (0.25), *Data: privacy* and *Learning performance* (0.31 each). The clusters *Teacher awareness* (0.41), *Learning support* (0.45) and *Learning outcome* (0.46) are all similar in range. The cluster with the by far highest bridging values and thus least coherence is *Acceptance & uptake* (0.86). In order to get a better grasp of the different clusters, a more detailed description of their characteristic statements is given below.

### Cluster Descriptions

Cluster 1 *Data: open access* contains eleven statements with bridging values ranging from 0.06 to 0.60. Most statements deal with aspects of openness and transparency of the used data as well as the used algorithms, e.g., “that data are open access”, “portability of the collected data”.

Cluster 2 *Data: privacy* is about exactly that: privacy, control of data, and transparency of data access. There are eight statements in the cluster with bridging values ranging from 0.10 to 0.72. Representative statements are “that privacy is ensured”, “if learners can influence which data are provided”.

Cluster 3 about *Acceptance & uptake* contains 13 statements and is very diverse as can be seen from the bridge value range from 0.66 to 1.00. The cluster describes aspects of acceptance of LA and its results by different stakeholders but also the comparability of methods or the context and objectives dependence of LA. An example statement is “that administrators invest in scaling successful tools across their programming”.

Cluster 4 *Learning outcome* is also somewhat diverse with a bridging value range from 0.19 to 0.87. It contains 13 statements that deal with comparability of LA results, teacher motivation, result accuracy and feedback for teachers, e.g., “if teachers are able to gain new insights using the given LA methods”, “that LA results are compared with other (traditional) measures”.

Cluster 5 *Teacher awareness* consists of twelve statements with bridging values from 0.18 to 0.73. Most statements are connected to teachers changing their course material or their teaching behaviour in response to LA results about their students: “that teachers change their behaviour in some aspects”, “that teachers react in a more personalized way to how their students are dealing with learning material”.

Cluster 6 *Learning performance* is one of the smallest clusters as it consists of only eight statements. The bridging value range is relatively small, i.e., 0.11 to 0.59. Statements in this cluster are about student performance, learning

and achievement improvement. Representative statements are “that change in workplace learning is measurable”, “the extent to which the achievement of learning objectives can be demonstrated”.

Cluster 7 *Learning support* is a very stable but also rather large cluster with 18 statements. Its bridging values range from 0.14 to 0.76. Statements in this cluster are often formulated generally and deal with support for teachers as well as for students, e.g., “an early detection of students at risk”, “the ability to explain what could help to further improve”, “that students regularly utilize the tools provided”.

Cluster 8 about *Student awareness* is the largest and most coherent cluster. It contains 20 statements and its bridging value range is from 0.00 to 0.43. The cluster is also very stable and consistent. All statements are related to students, their achievement, success, self-regulation, awareness, learning behaviour and motivation, e.g., “that students become more self-regulated in their learning processes”, “that students are more aware of their learning progress”.

## Rating Maps

Once the cluster map is settled upon, the experts’ ratings of the quality indicators can be included in the calculation as well. Two aspects were given to the experts to be rated on a scale from one to seven (one for a low, seven for a high rating): *importance* and *feasibility*. While the former refers to the priority or importance of a quality indicator in relation to the evaluation of effects of LA, the latter indicates the perceived ease of applicability of a quality indicator. The GCM tool automatically applies the experts’ ratings to the cluster map, indicating the importance or feasibility by layering the clusters. The system always divides the ratings into five layers based on the average ratings provided by the participants for the rating maps. The anchors for the map legend are based on the high and low average ratings across all of the participants. One layer indicates a low rating, whereas five layers indicate a high rating of the respective aspect.

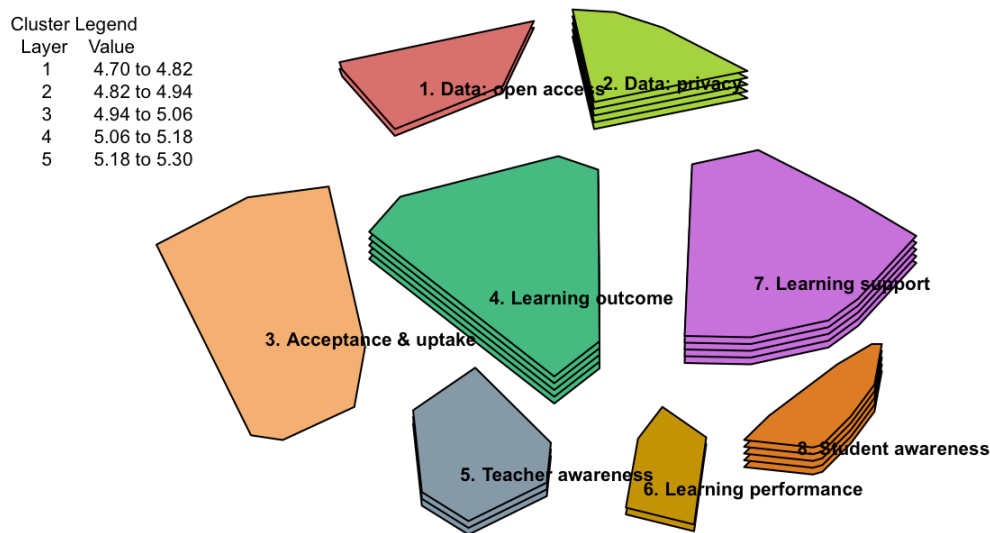


Figure 4: Rating map on *importance*

Figure 4 shows the rating map according to the *importance* aspect. Clusters *Data: privacy*, *Learning outcome*, *Learning support*, and *Student awareness* each received very high importance ratings as they all have five layers. *Teacher awareness* has three layers, while *Data: open access* and *Learning performance* have two layers each and *Acceptance & uptake*, i.e., the least coherent cluster, has only one layer.

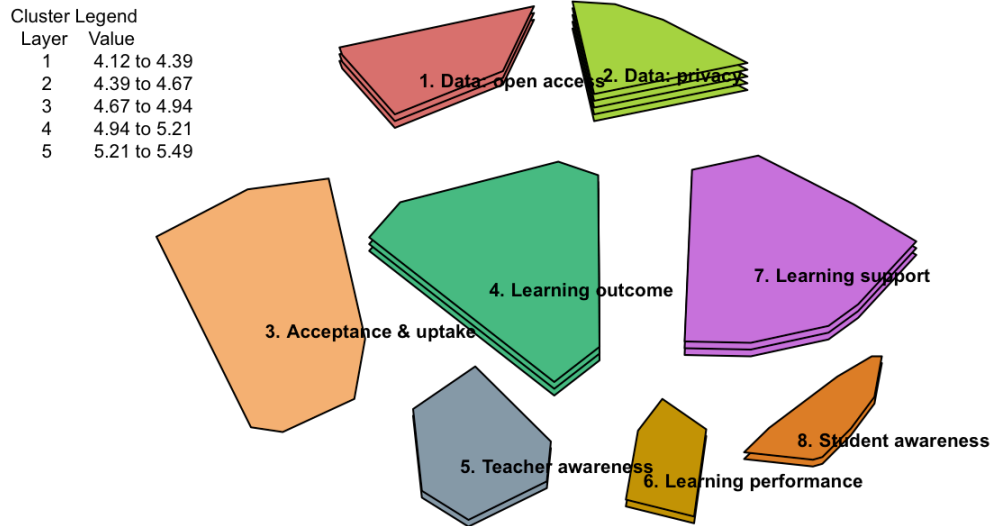


Figure 5: Rating map on *feasibility*

Looking at the *feasibility*-rating map (see Figure 5) one can see a change in the rating behaviour of the experts. Although the *Data: privacy* cluster also gets five layers and is thus deemed highly feasible by the experts, the other three very important clusters have been rated less feasible: *Learning outcome* and *Learning support* only receive an intermediate level of feasibility with three layers each. *Student awareness*, a highly important cluster, receives a low feasibility rating with two layers only. *Teacher awareness* also drops down to two layers. The cluster dealing with *Acceptance & uptake* was seen as neither important nor feasible by the experts. The only cluster that receives more layers in the *feasibility*-rating map is *Data: open access* and is thus deemed more feasible than it is important.

A ladder graph (see Figure 6) offers a form of visualisation that is well suited to compare the clusters' ratings according to *importance* and *feasibility*. The rating values are based on a cluster's average rating. A Pearson product-moment correlation coefficient ( $r = 0.65$ ) indicates a strong positive relationship between the two aspects of importance and feasibility. For both ratings, the *Data: privacy* cluster receives the highest values while *Acceptance & uptake* receives the lowest. As was already observable from the rating maps, the three clusters about *Learning outcome*, *Learning support* and *Student awareness* have all been rated as very important but as much less feasible.

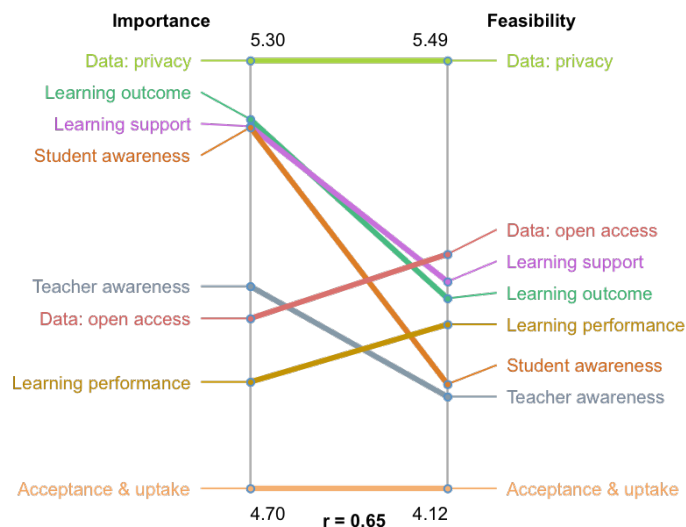


Figure 6: Ladder graph of the rating values for the clusters

A third visualisation the GCM tool offers for the rating aspects are so-called go-zones, i.e., bivariate graphs that allow to explore the statements in relation to their ratings more deeply. A Go-zone graph maps each statement onto a space between x- and y-axis based on the mean values of the two rating aspects of *importance* and *feasibility*. Go-



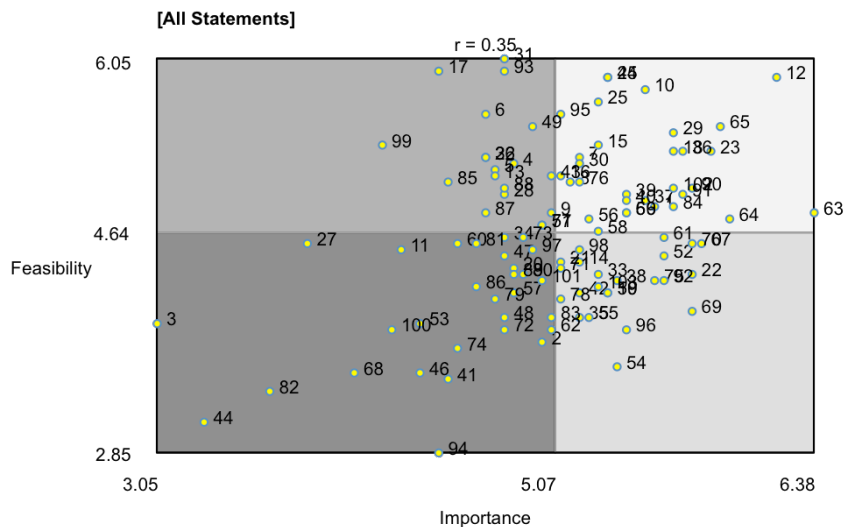


Figure 7: Go-zone graph of all 103 statements

## Constructing a Framework of Quality Indicators

## Discussion of the Group Concept Mapping Outcomes

Looking at the clusters in Figure 3, their coherence is also observable visually. One can see that the four most coherent clusters (*Data: open access*, *Data: privacy*, *Learning performance* and *Student awareness*), i.e., the ones with smaller bridging values, are the smaller ones in relation to area size and that the three least coherent clusters (*Acceptance & uptake*, *Learning outcome* and *Learning support*), i.e., the ones with higher bridging values, are much larger in area size. The two most stable clusters are the ones about *Learning support* and *Student awareness*, i.e., they both remained stable until the five-cluster solution while the others merged. This implies a fairly high agreement between the experts' sorting and the system's multidimensional scaling and hierarchical clustering. We therefore take cluster coherence and stability to be a first indication of relevance when trying to find quality indicators for learning analytics.

Also very interesting conclusions can be drawn when comparing the two rating maps (see Figure 4 and Figure 5) with one another. The *Acceptance & uptake* cluster received low ratings for *importance* as well as for *feasibility*. The experts' low rating is also supported by the cluster's coherence. With an average bridging value of 0.86 and individual statement bridging values spanning from 0.66 up to 1.00, the cluster contains a rather diverse collection of statements. When trying to create quality indicators to evaluate effects of learning analytics we therefore focused on all other clusters first in order to find suitable criteria before taking this cluster into account as the indicators it contains are too incoherent, too vague, unimportant and unfeasible as a group.

This leaves us with a slightly different but nonetheless very interesting cluster landscape: The two clusters in the North (1, 2) both deal with data, access, methods, algorithms, transparency and privacy, i.e., with technical issues, while the clusters in the South (5, 6, 8) deal with awareness, reflection, performance and behavioural change of students and teachers, i.e., with human issues. The “technical North” (*Data: open access* and *Data: privacy*) and the “human South” (*Teacher awareness*, *Learning performance* and *Student awareness*) are bridged by a wide layer of learning-related clusters (*Learning outcome* and *Learning support*). Apart from the North-South view, one can also look at the map with an East-West perspective: The three Eastern clusters (*Data: privacy*, *Learning support* and *Student awareness*) are more concerned with issues during the learning process while the Western clusters (*Data:*

*open access*, *Learning outcomes*, *Teacher awareness* and *Learning performance*) are slightly more concerned with issues of learning output and results. This division is of course not to be seen strictly, but these groupings clearly show a thematic tendency. As for the construction of the framework, we conclude that the aspects of technology, stakeholders (humans), learning processes and learning outcomes should all be reflected in the criteria.

Taking the two rating aspects *importance* and *feasibility* into account, we get two different versions of the landscape described above. The *importance* map on the left side of Figure 8 clearly shows that the learning-related middle layer, i.e., the clusters about *Learning outcome* and *Learning support* within the dashed line, is deemed highly important by the LA experts. But all Eastern clusters, i.e., the ones about *Data: privacy*, *Learning support* and *Student awareness* within the dotted line, also receive five layers of *importance*. Generally one can thus say that the focus of *importance* is on the learning process-related clusters. For the *feasibility* map on the right side of Figure 8 the landscape shifts. Now there is a clear North-South divide: The technically-oriented clusters in the North (dotted circle) are deemed most feasible by the experts, followed by the learning-related layer in the middle (short dashed circle) and concluded by the human-related clusters in the South (long dashed circle). This again supports the construction of the framework's criteria according to the data-learning support & process-stakeholder view.

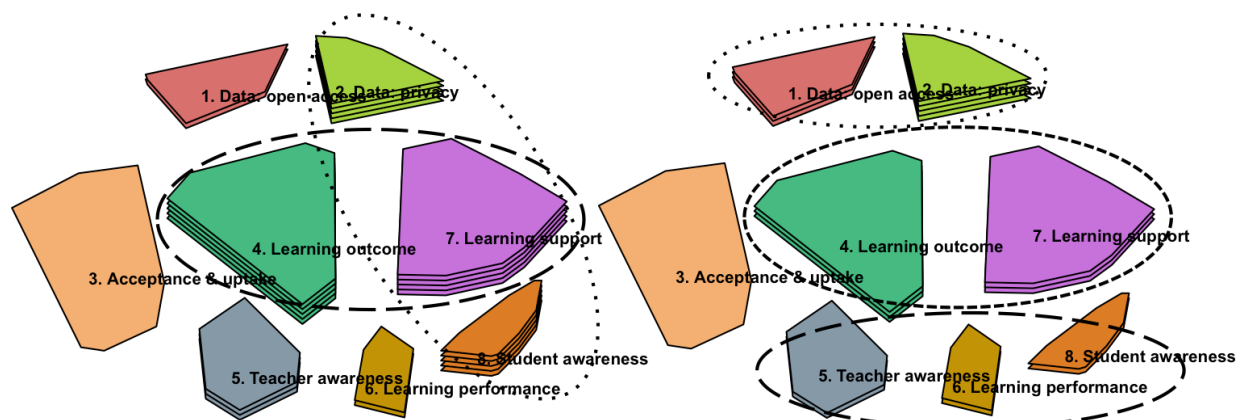


Figure 8: Comparison of the rating maps of *importance* (left) and *feasibility* (right)

Looking at the ladder graph in Figure 6 allows a closer look at the differences in average ratings for the different clusters. Especially the drop in *feasibility* compared to *importance* for a number of clusters is quite obvious. The most striking drop is that of the *Student awareness* cluster. The experts think student awareness to be quite an important aspect to take into consideration when evaluating effects of LA theoretically but deem it difficult to apply in real world settings. This can be explained with the fact that many teachers, and thus very likely also the LA experts involved in this study, do not think students to be capable enough of judging their own learning processes and progresses as it has been identified by Drachsler & Greller (2012).

When deciding upon the criteria of the framework it is important to find a good trade-off between the *importance* ratings and the *feasibility* ratings. Due to the high *importance* of the clusters about *Data: privacy*, *Learning outcome*, *Learning support* and *Student awareness* it seems to be sensible to use them as a basis for the criteria of the framework. The *feasibility* ratings of the clusters can then be used to associate the remaining clusters with these four criteria: The *Data: privacy* cluster is by far the most feasible one, followed by the *Data: open access* cluster. The two can thus be combined into one data criterion. The next two clusters on the *feasibility* scale are *Learning support* and *Learning outcome*, two of the criteria candidates that stay on their own due to their high *importance* rating. As the latter cluster is followed by the *Learning performance* cluster and as they both deal with learning results and effects, it makes sense to construct a combined criterion from them. The next cluster on the feasibility scale is *Student awareness*, closely followed by *Teacher awareness*. Both of them are “human clusters” and concerned with awareness, reflection and behavioural change. They can therefore be combined into one criterion even though they address different stakeholders.

## Outline of the Framework

From the results of the GCM study we can identify four topic areas that can be turned into criteria for the framework: the first deals with anything related to data, algorithms, transparency and privacy. It is based on the clusters *Data: privacy* and *Data: open access*. For the sake of simplicity the criterion is called *Data Aspects*. It contains the quality indicators *Transparency*, *Data Standards*, *Data Ownership*, and *Privacy*. The second topic area concerns support for students and teachers during the learning process, i.e., while using LA tools. It is entirely based on the *Learning Support* cluster and also takes over this name. The quality indicators of this criterion are *Perceived Usefulness*, *Recommendation*, *Activity Classification*, and *Detection of Students at Risk*. The third topic area deals with the results at the end of the learning process, i.e. any issues of output, consequence, performance, outcome etc. In this case, however, it is not primarily to be seen in relation to individual student performance, e.g., their grades, but refers to the LA tools' results and outcomes. It is comprised of the two clusters *Learning outcome* and *Learning performance*. The criterion is named *Learning Measures and Output* and contains the quality indicators *Comparability*, *Effectiveness*, *Efficiency*, and *Helpfulness*. The fourth topic area contains the quality indicators *Awareness*, *Reflection*, *Motivation*, and *Behavioural Change* of students and educators during the learning processes, i.e., it is about the educational aims identified at the beginning of this article. This criterion is called *Objectives*.

Most statements related to stakeholders are about learners and teachers and hardly about institutions. This is partly due to the fact that we did not take the cluster *Acceptance & uptake* that contains some statements about this into account right away. It is also due to such statements being spread over all clusters. As we consider indicators of organisational issues to be an important aspect when considering the evaluation of LA tools (cf. Arnold et al., 2014a), we decided to add a fifth criterion to the framework: *Organisational Aspects* containing the quality indicators *Availability*, *Implementation*, *Training of Educational Stakeholders*, and *Organisational Change*.

The quality indicators are based on a review of the statements in the go-zone graphs of each cluster. In most cases these indicators can be found in the upper right quadrant of the go-zone graphs. In some cases statements from the only feasible or only important quadrant were chosen as well if they are close to the important and feasible quadrant. The statements chosen for each criterion are then combined and turned into slightly shorter, more general statements that clearly represent a quality indicator for a given criterion. Figure 9 shows a first outline of the five criteria with their four quality indicators.

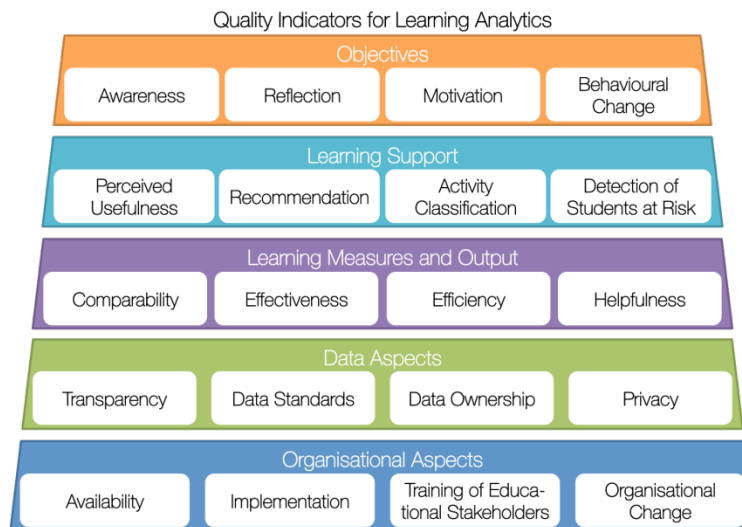


Figure 9: First outline of the framework of quality indicators for learning analytics

## Literature Supporting the Criteria

In this section we present a focused literature review to further extend the GCM study with the latest insights from the LA community. It is structured according to the different layers of the framework. Although the three criteria *Objectives*, *Learning Support*, and *Learning Measures and Output* are clearly separable from one another in regards to their quality indicators and purposes, it is often difficult to exclusively attribute findings from the literature to one of the criteria only. Literature concerning these three layers has therefore been combined into one section.

### Objectives, Learning Support, and Learning Measures and Output

Some works on awareness (e.g., Endsley, 1995, 2000; Charlton, 2000) and reflection (e.g., Schön, 1983; Bolton, 2010) have already been mentioned in the introduction of this article. They all deal with these educational and pedagogical concepts in general and are not directly attached to the domain of LA. Their findings, however, matter to this domain. McAlpine & Weston's (2000) work also deals with reflection as a general concept in educational settings. They argue that "reflection is not an end in itself, but a mechanism for improving teaching and hence maximizing learning".

Studies in the related domain of technology-enhanced learning reveal several aspects that can be used for outcome measurement of recommender systems (Drachsler, Hummel, & Koper, 2009) but could also be used for the analysis of other educational technologies and LA tools. The first measurement category is a technical one with the parameters of accuracy, coverage and performance. The second measurement category covers educational aspects and involves the parameters of effectiveness, efficiency, satisfaction and drop-out rate. Social network measures form the third category with parameters of variety, centrality, closeness and cohesion.

Clow (2012) points out that "learning analytics should generate metrics that relate to what is valued in the learning process. If the final assessment rewards undesired behaviour, improving the control system to more effectively optimise the results will make the learning worse". Clow therefore identifies three strategies by which the effectiveness of LA can be improved: (1) enhancement of the speed of response, e.g., real-time feedback rather than summarising feedback, (2) enhancement of the scale of response, e.g., feedback to more than one stakeholder, and (3) improvement of the quality of an intervention, e.g., testing of the intervention or participation of more stakeholders.

Course Signals is an early intervention solution for collegiate faculty (Arnold & Pistilli, 2012) and serves as an example tool of implemented LA. With this tool, teachers can provide feedback to students about their performance and predicted progress. The feedback is comprised of a personalised email and a progress visualisation, i.e., a traffic light signal. Courses that used the tool showed a strong increase in positive grades and at the same time a decrease in negative grades and withdrawals. Both with teachers and with students, Course Signals received positive overall experiences although teachers approached it with more caution than students.

This caution can be set in relation to the findings of a survey among teachers and researchers of LA. The study revealed that "trust in learning analytics algorithms is not well developed" yet (Drachsler & Greller, 2012). Many educators hesitate to take the calculations of algorithms about learning and educational effects as valid while at the same time they hope to gain new insights from those analytics results. The study also showed that for many participants the application of LA cannot provide a more objective assessment than they could do on their own and that a proper assessment of a learner's state of knowledge is not possible.

A combination of LA and action research to support teachers in educational settings is presented by Dyckhoff, Lukarov, Muslim, Chatti, & Schroeder (2013). They describe possible effects of learning analytics on teaching and investigate how this could be evaluated. For them, LA tools should be useful to achieve the set goals in a given context. Their findings show that in many cases LA tools do not yet answer all of the questions that teachers have in regard to their educational setting. This especially concerns qualitative analysis as well as data correlation from different source. Quantitative results, however, are often easily available. Among others, the authors relate these shortcomings to an insufficient involvement of teachers in the design process of LA tools and the lack of appropriate, diverse data sources, e.g., student profile data, mobile data. They conclude that "there is a necessity for creation of

evaluation tools to measure the impact and effects of LA on the learning process” and for mechanisms to support and reassure awareness and reflection, as well as to improve teaching processes.

An example of work dealing with the design of pedagogical interventions is that of Wise (2014). The author presents four principles of pedagogical learning analytics intervention design: (1) integration, (2) agency, (3) reference frame, and (4) dialogue. Teachers and course developers can build upon these principles in order to support students in productively making use of LA. Wise also describes three core processes that students should be engaged in: (1) grounding, (2) goal-setting, and (3) reflection. The principles together with the core processes form a model of pedagogical LA intervention design.

## **Data Aspects**

One important aspect when dealing with data-related criteria is the availability of data sets and data standards. While a few years ago, open access to data sets was hardly constituted (Drachsler et al., 2010), the last few years have shown an immense rise in the availability of and open access to data sets for the technology-enhanced learning, LA and educational data mining domains. Verbert, Manouselis, Drachsler & Duval (2012) provide an overview of existing datasets and analyse them along the dimensions of their framework for the analysis of educational datasets. There are three dimensions: (1) dataset properties, (2) data properties, and (3) learning analytics objectives. Several initiatives are now offering access to educational data sets such as the LinkedUp Project (2014) with its LinkedUp Dataset and LinkedUp Data Challenge, the LAK Dataset (Taibi & Dietze, 2013), the DataHub (n.d.) and the PSLC DataShop (Koedinger et al., 2010).

A number of legal, risk and ethical issues that should be taken into account when implementing LA at educational institutions in the United Kingdom is presented by Kay, Korn & Oppenheim (2012). They describe that these institutions have to find a balanced way to assure educational benefits, that they are under as much competitive pressure as organisations in the consumer world and that they need to satisfy the expectations of the now arising born digital generations of learners. The authors suggest four principles that provide good practice when tackling the above-mentioned conflicts: (1) clarity, (2) comfort and care, (3) choice and consent, and (4) consequence and complaint.

Willis, Campbell & Pistilli (2013) apply *The Potter Box*, i.e., an ethical model in business communications, to LA. They conclude that institutions will have to “balance faculty expectations, various federal privacy laws, and the institution's own philosophy of student development. It is therefore critical that institutions understand the dynamic nature of academic success and retention, provide an environment for open dialogue, and develop practices and policies to address these issues”.

During the EDUCAUSE IPAS Summit in 2013 participants were asked to discuss issues associated with managing risk in student success systems and to identify opportunities for the development of such systems (EDUCAUSE IPAS Summit Report, 2014). More specifically, the discussions focused on three aspects: (1) the identification of internal and external drivers that encourage the implementation of LA, (2) the identification of institutional risks, documentation of effective practices and review of existing and new solutions, and (3) the development of strategies that already take risk issues into account during the design of LA processes. The authors conclude that existing and new data sources have to be integrated in a better way and that educational institutions should know exactly which data they collect for what purpose and who has access to that data. Institutions should also address the movement of students and their data between institutions and should not misuse the collected data to predetermine a student's success.

An analysis of how privacy and ethical issues specific to the context of learning analytics and its related research as well as guidelines about how to comply with common privacy principles are presented by Pardo & Siemens (2014). These principles are conceived from the review of LA proposals, government frameworks and regulatory directives and allow educational institutions to assess their current level of compliance in order to then possibly improve their privacy-related matters. The principles are: (1) transparency, (2) student control over data, (3) right of access / security, and (4) accountability and assessment.

Also relevant for the *Data Features* criterion is the methodology based on value-sensitive design that incorporates ethical and legal considerations and requirements throughout the research and development cycle of technology as Friedman (1997) explains. Value-sensitive design is the idea that ethical analysis and reflection needs to take place when and where it can make a difference for the design and governance of technology: starting early on in the design and development process, and close to where the technology is being shaped and designed. Ethical considerations concern first of all the privacy of individuals taking part in the system. A high degree of configurability, the provision of meaningful default options that relate to a privacy-by-default approach, combined with informative explanations given to users are some of the ingredients that will allow the achievement of the notion of informed consent (Van den Hoven, 2008).

## **Organisational Aspects**

In the 21<sup>st</sup> century, more and more higher education organisations apply LA to optimise student success. According to Norris & Baer (2013) such intelligent investments from the organisations have a strong and justifiable return on investment: the implementation of enhanced analytics is to be seen as critical for student success on the one hand and achieving institutional effectiveness on the other as without it, organisations cannot meet the current gold standard for institutional leadership. Norris & Baer conducted a survey among institutional practitioners and vendors about the building capacity in analytics to improve student success and how they determine the state of practice and gaps between needs and solutions. They interviewed 40 leading institutions from the American higher education sector as well as 20 technology vendors and came up with a framework for optimising student success through analytics that contains seven elements: (1) manage the student pipeline, (2) eliminate impediments to retention and student success, (3) utilise dynamic, predictive analytics to respond to at-risk behaviour, (4) evolve learner relationship management systems, (5) create personalised learning environments / learning analytics, (6) engage in large-scale data mining, and (7) extend student success to include learning, workforce, and life success.

In their discussion paper, Siemens, Dawson & Lynch (2013) present a national LA strategy to the Australian Government after undertaking a four step process: First, they evaluated the benefits of analytics in other sectors than education, then had a closer look at the data collection policies on provincial, territory, state and national level, followed by a review of universities around the world that are already developing analytics strategies, and finally, they inspected the role corporate partners can play in helping universities achieve analytics competence. Their five final suggestions are: (1) Australian higher education leaders should coordinate a high level learning analytics task force with a variety of stakeholders, (2) existing national data and analytics strategies should be leveraged, (3) guidelines for privacy and ethics should be established, (4) a coordinated leadership program should be set up, and (5) open and shared analytics curricula should be developed with the learning analytics community. Although their paper focuses on the LA situation in Australia, the findings can be applied to other countries as well.

Arnold, Lonn & Pistilli (2014a) tackle the readiness of institutions to implement LA. Instead of only looking at the maturity of an institution's already implemented LA solution, the authors try to investigate how institutions that do not apply any analytics yet can become mature to do so. Their Learning Analytics Readiness Instrument (LARI) survey was conducted at nine higher education institutions and focuses on five readiness components for LA implementations: (1) ability, (2) data, (3) culture and process, (4) governance and infrastructure, and (5) overall readiness perception.

With the help of LA educational institutions are able to tune or correct the inner workings of their programs. Méndez, Ochoa & Chiluiza (2014) present five techniques that allow institutions to gain such insights: (1) difficulty estimation, (2) dependence estimation, (3) curriculum coherence, (4) dropout and enrolling paths, and (5) a load/performance graph. For their example analysis the authors used data from 2543 undergraduate computer science students at the ESPOL University in Ecuador spanning from 1978 until 2012. With their large study the authors want to show how simple analytics can be used to re-design whole program curricula.

Finally, in their panel discussion at LAK 2014, Arnold et al. (2014b) argue that “in order to truly transform education, learning analytics must scale and become institutionalized at multiple levels throughout an educational system”. During the discussion, panel participants focused on five areas related to the adoption of LA: (1) technology infrastructure, analytics tools and applications, (2) policies, processes, practices and workflows, (3) values and skills, (4) culture and behaviour, and (5) leadership. From the discussed case studies the authors conclude that institutions

have to put effort and intention into planning the implementation and adoption of LA. They suggest using existing research and theory as a foundation when beginning to build new theories and research about system level thinking.

## Conclusion

This article proposes a first outline of a five-dimensional framework of quality indicators for learning analytics to help standardise the evaluation of LA tools. The work was motivated by the lack of evaluation standards that define quality indicators of LA tools. After introducing the objectives of LA, we presented a GCM study with experts from the LA domain to identify a list of quality indicators. With the help of a number of analysis steps within the GCM tool we first created a point map of the statements that we then turned into a cluster map including cluster labels. The experts' ratings on importance and feasibility of the statements allowed us to further narrow down the list of possible quality criteria as well as indicators. After taking the rating maps, the ladder graph and the go-zone graphs into account, we were able to propose a first outline of the framework (see Figure 9) with the following five criteria and quality indicators: *Objectives* (Awareness, Reflection, Motivation, Behavioural Change), *Learning Support* (Perceived Usefulness, Recommendation, Activity Classification, Detection of Students at Risk), *Learning Measures and Output* (Comparability, Effectiveness, Efficiency, Helpfulness), *Data Aspects* (Transparency, Data Standards, Data Ownership, Privacy) and *Organisational Aspects* (Availability, Implementation, Training of Educational Stakeholders, Organisational Change). In order to extend the found criteria we conducted a focused literature review to show their usage within the community so far.

Limitations of our current approach are related to the participants of our GCM study: Most participants work at a university and are more research- than practice-oriented. It would be interesting to see whether and how the framework and its quality indicators would change if (high) school teachers and/or more practice-oriented university staff were involved in the process.

For our future research we first aim to further extend the literature study to complement the quality indicator framework by analysing the most recent empirical studies on LA according to their evaluation criteria and quality indicators. Ultimately, we aim to transfer the findings into a concrete evaluation instrument that also includes methods for LA stakeholders to test the indicators. Initial applications of the evaluation instrument will be done in higher education institutions first but we will also try to collect experiences in the K12 and commercial sector. A good mean for this approach is the Learning Analytics Community Exchange project (LACE, 2014) that focuses on the exchange of best practises within these sectors.

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